MINIMALLY PARAMETRIZED META-HEURISTIC OPTIMIZATION TECHNIQUE FOR TUMOR SEGMENTATION IN MR BRAIN IMAGES

A SYNOPSIS

Submitted by

N. SENTHILKUMAR

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(DEEMED TO BE UNIVERSITY)

ANAND NAGAR, KRISHNANKOIL – 626 126

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1. INTRODUCTION

As per the recent findings by the International Association of Cancer Registries (IARC), about 19.3 million individuals across the globe were infected (new cases reported) by cancer in 2020, and the rate is expected to increase by 56.8% to reach 30.2 million by 2040. In particular, over 3,08,102 individuals were diagnosed with brain and nervous system-related tumours in 2020, and the same was projected to grow to 4,15,183 in the year 2040 [1]. Of these, about 8% are children below the age of 14.

Therefore, early detection of the tumour is highly recommended as it increases the chances of successful treatment. The medical image processing field has become vital as the medical images essentially help the anatomist in the image-driven pre- and post-surgical assessments of tumour treatment. Various medical imaging techniques [2], such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), X-Ray, Ultrasound Imaging, Functional Magnetic Resonance Imaging (fMRI), etc., were widely used to assess the severity of the tumour. Among different imaging modalities, medical practitioners prefer MRI for the segmentation of patients' pathologies due to its high ability to categorise normal and abnormal tissues. However, in addition to the imaging data, the medical practitioner needs specialised and customised graphical tools to accurately detect tumour regions and initiate treatment procedures [3], such as surgical intervention, radiotherapy, and chemotherapy, scrupulously.

Although many automatic segmentation [4] algorithms have been developed in previous studies to comprehend tumour characteristics like volume, size, shape, type, and location, in addition to the segmentation process, the image is needed to optimize post-segmentation to achieve the desired results for further assessment. To overcome the abovementioned problems, minimally parameterized optimization algorithms, such as the JAYA algorithm, have been recommended in the study.

2. LITERATURE REVIEW

This segment provides the findings and assessments of certain recently developed image segmentation and optimization techniques proposed in the literature for a holistic view and a better understanding.

Soltani-Nabipour et al. [5] applied an improved region-growing method to computed tomography images collected from four patients and achieved a segmentation accuracy of 98%. Punitha et al. [6] developed a novel segmentation technique using an optimized region growth algorithm to detect benign and malignant breast cancer. The proposed algorithm was implemented on 300 images and yielded a sensitivity of 98.1% and a specificity of 97.8%.

Zhang et al. [7] have successfully verified a system to separate vein and non-vein regions in the finger using the active contour method. In addition to this, the initial level of segmentation is performed using the Kernel Fuzzy C-Means (KFCM) algorithm in order to avoid the local minima limitation due to the initial contour position. The system has achieved an accuracy of 95.41% with a false acceptance rate of 1%.

Modified level set-based MR brain image segmentation is presented by Virupakshappa, and B. Amarapur, [8]. In the proposed model, the authors developed an automatic scheme to find the initial contour position based on the histogram value obtained from the target image. This helped to segment the MR image with a high level of homogeneity and 99% accuracy.

A.Z. Atiyah, and K. H. Ali, [9] have proposed an image segmentation algorithm using the U-Net architecture, in which the authors have utilised two methods: region growing and edge detection for the segmentation. The final scores of the recommended algorithm indicate that edge-based segmentation yielded superior results when compared to region-growing based segmentation. Khairandish et al. [10] developed a hybrid model using convolutional neural networks (CNN), and support vector machines (SVM) for the classification of MR images and a threshold-based method for initial segmentation. The hybrid framework obtained an accuracy of 98.4959%.

Díaz-Pernas et al. [11] performed the brain image segmentation using a deep convolutional neural network (DCNN), which has the ability to segment three different kinds of carcinoma, namely, gliomas, meningiomas, and pituitary tumours, with the help of three different spatial information models. The method utilised 3064 MR brain images with all three views (axial, sagittal, and coronal) from 233 patients and reported an identification accuracy of 97.3%.

Kavitha et al. [12] developed a novel hybrid GCPSO (Guaranteed Convergence Particle Swarm Optimization)-FCM algorithm that is applied to particles across a number of generations or iterations in order to increase the fitness value of all the

particles. The authors utilised bilateral multi-resolution transforms in both the pre-processing and segmentation stages. The authors achieved segmentation accuracy of 95.32% compared to other resolution-based methodologies.

Jai Shankar et al. [13] proposed a new algorithm for brain tumour detection through MRI images using a clustering algorithm based on the Bat Optimization Algorithm (BOA). The algorithm finds the centroids of a number of clusters, finds the global best, and updates the cluster centroids based on the echolocation of bats behaviour. Results of experimentation show that the suggested framework outperforms existing methods with 98.5% accuracy.

Alrosan et al. [14] modified the standard search operation of the standard ABC algorithm by computing the mean value of the best solutions obtained during the last search operation. The mean value is used to assign the best cluster head position for FCM segmentation. The proposed algorithm is tested on the 14 benchmark functions and also on the 20 real clinical MR brain image datasets with different levels of difficulty and domains. The suggested method recorded Tanimoto coefficients of 0.764 for white matters, 0.695 for grey matters, and 0.2172 for CSF.

Weiner filter and Lion optimizer are used by Surbhi et al. [15] to filter the image's distortions and find the ultimate fitness function. Fuzzy k-means with linear discriminant analysis in this approach helps in forming clusters with similar data and extracting the features from them for easy classification. Zhao et al. [16] used brain MR images to identify and extract context-sensitive characteristics and gradient features in high- and low-grade gliomas. On the BraTS 2015 dataset, the algorithm attained average specificity and sensitivity results of 73.66% and 87.7%, respectively.

Gudise et al. [17] presented a segmentation technique to distinguish WM, GM, and CSF regions from MR brain image-based TLBO algorithms. In this teaching-learning-based optimization algorithm, the authors have optimized the variables efficiently, which were fuzzy valued earlier. The proposed technique has outperformed other optimization techniques like the Bacterial Foraging Algorithm (BFA), Particle Swarm Optimization (PSO), Electromagnetic Optimization (EMO), and Genetic Algorithm (GA).

A. Kapoor, and R. Agarwal [18] designed a technique for automatic identification and image segmentation of MRI scans specifically for pathological regions. Initially, in the pre-processing stage, intensity-based image contrast enhancement was utilized. Then image segmentation is done through the K-means

technique, and then both the PSO and Firefly methods are performed separately to identify the pathological regions. The method showed an accuracy of 97%. Finally, an in-depth comparison has been carried out on the individual outcomes of the PSO and Firefly methods.

V. Rao [19], developed an optimization algorithm for solving constrained and unconstrained optimization problems. This algorithm requires only the common control parameters and does not require any algorithm-specific control parameters. The performance of the proposed algorithm is investigated by implementing it on 24 constrained benchmark functions with different characteristics, and the performance is compared with that of other well-known optimization algorithms.

Dahiya et al. [20] analysed the three combinations of single or multi-objective k-means with conventional or modified ABC to identify the tumour in brain MR images. With the help of colour labelling, the input monochrome image is converted into a coloured one, which helps in more precise tumour segmentation. The multi-objective modified ABC produces an average accuracy, sensitivity, specificity, F-measure, precision, and computational time of 96%, 98.9%, 64%, 94%, 92%, and 5.9 seconds, respectively.

Problems encountered with the above segmentation algorithms include (i) strong perception of noise and artifacts; (ii) higher processing time; (iii) lower accuracy in noisy images; (iv) loss of WM, GM, and CSF parts during segmentation; (v) lack of robustness in optimization; and (vi) cluster overlapping.

Despite all of the potential and advantageous applications of deep learning approaches, some areas remain to be explored. This research concentrates on unexplored options in the use of deep learning, and it has been very influential in the outcome of several meta-heuristic algorithms using JAYA optimization and modified forms of fuzzy clustering for complex processes such as tumour region recognition and tissue segmentation in MR brain images. In this analysis, significant progress was made, and the outcomes were substantiated using all available performance measures.

3. OBJECTIVES

The main objectives of the research are as follows:

I. To segment the tumour portions in an MR brain image using a modified version of the novel JAYA optimization algorithm.

II. To reduce the overall convergence computation cost by using the fewest possible control parameters (JAYA algorithm).

III. To develop a fully automatic system with dual metaheuristic optimization techniques to segment brain MRI with a higher success rate than the single optimization algorithm.

IV. To address the exploitation and exploration limitations confronted by the optimization algorithms during search operations with suitable modifications to their standard operations and,

V. To dissect the infectious region from MRI using the self-accommodative JAYA optimization algorithm based on modified FCM.

4. RESEARCH PROBLEM

MRI can aid in the diagnosis of a brain tumour; however, if the tumour is engrossed by edema in the scan, radiologists may struggle to pinpoint the exact location of the tumour because it is obscured by voluminous tissues and edema. A standard image analysis method available in an imaging centre cannot even segment healthy tissue portions. In these kinds of situations, the diagnosis will be prolonged, and if the procedure is also assertive, the patient's survival period may decline. Furthermore, as the dataset to be diagnosed increases, the radiologist's task will become more erratic. So, there is a need for a fully automatic and efficient algorithm to segment tumour, tissue, and edema regions in all kinds of MRI, such as T1-W, T2-W, and FLAIR.

5. CONTRIBUTIONS

Totally 25 high- and low-grade brain MR images from the BraTS 2013 dataset, 21 MRI slices from the Harvard Brain Web Repository, and 25 clinically purposed brain images with primary neuro-ectodermal carcinoma, meningioma carcinoma, and astrocytoma carcinoma complaints are used in this work.

5.1. A novel triple-level combinational framework for brain anomaly segmentation to augment clinical diagnosis

The proposed algorithm offers better support to a radiologist in the process of diagnosing pathologies since it utilises both optimization and clustering techniques. JAYA and FCM are the optimization and clustering techniques used to render efficient

MR brain image analysis. Firstly, the image is smoothed and filtered via a Gaussian filter. Secondly, the initial level of clustering is done using the FCM algorithm. Thirdly, texture-based features are extracted from the segmented MR brain image using GLCM. Fourthly, a novel JAYA algorithm is used to find the optimal threshold values. Fifthly, based on the optimum threshold values obtained from the JAYA algorithm, a re-evaluation of FCM is done. Finally, the image is re-segmented, and the gold standard validates the fragmented tumour portion.

In this work, the novel JAYA algorithm helps in identifying the optimum threshold value based on which the cluster centre is updated in the FCM algorithm. The segmentation result of the FCM algorithm is further improved by the inclusion of the GLCM feature and the JAYA algorithm.

Though the proposed algorithm has a limitation in terms of inferior MSE value, the outcomes of the JAYA-based FCM algorithm remarkably identify and successfully segment the tissue regions. Robust segmentation was achieved by combining FCM for segmentation, GLCM for feature extraction, and the highly efficient Jaya Algorithm (JAYA) for optimization, and this is the key contribution and novelty of the proposed algorithm.

Figures 1a to 1e depict the good level of segmentation of the patient's MR brain image using the JAYA-FCM algorithm. Table 1 illustrates the Assessment comparison of the key parameters.

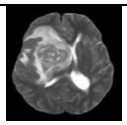
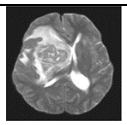
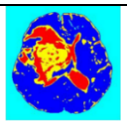
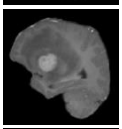
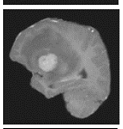
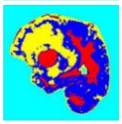
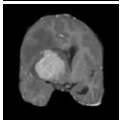
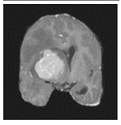
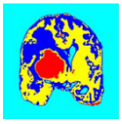
Image Planes	**Input Image**	**Filtered Image**	**FCM Output**	**JAYA-FCM Output**
T2-W Axial				
T1-W Sagittal				
T1-W Coronary				

Figure 1a: Qualitative output of segmentation of tumor region, WM and GM in MR brain image affected with Astrocytoma carcinoma

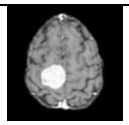
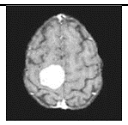
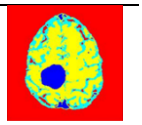
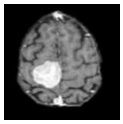
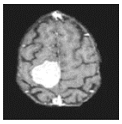
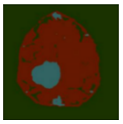
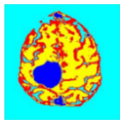
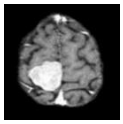
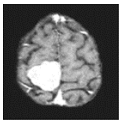
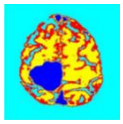
Contrast Enhanced (CE) Image Planes	Input Image	Filtered Image	FCM Output	JAYA-FCM Output
Axial: T1 (W)				
Axial: T1 (W)				
Axial: T1 (W)				

Figure1b: Segmented output of MR images with low and high-grade gliomas

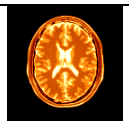
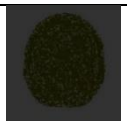
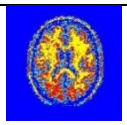
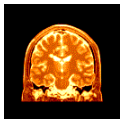
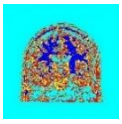
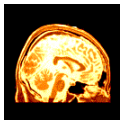
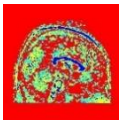
Image Planes	Input Image	Filtered Image	JAYA-FCM Output
Axial (or) Transverse			
Coronal			
Sagittal			

Figure 1c: Segmented output of the suggested algorithm processed on T2-Weighted MR images with a 1% noise level

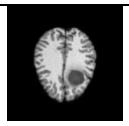
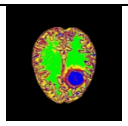
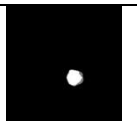
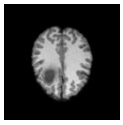
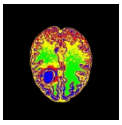
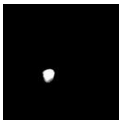
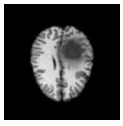
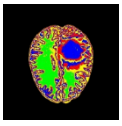
Image Planes	Input Images	FCM output	JAYA-FCM Results	Detected Tumor Region	Ground Truth Images
Axial: T1(W)					
Axial: T1(W)					
Axial: T1(W)					

Figure 1d: Examples of segmented output of the MR brain image with high-grade tumor acquired from BraTS 2013 dataset.

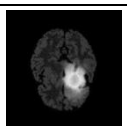
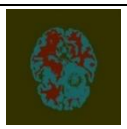
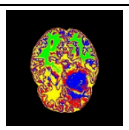
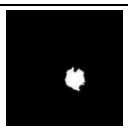
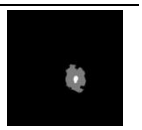
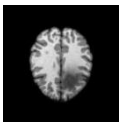
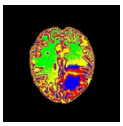
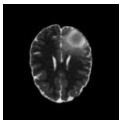
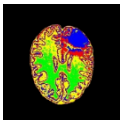
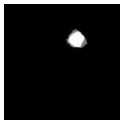
Image Planes	Input Images	FCM	JAYA-FCM Results	Detected Tumor Region	Ground Truth Images
Axial: FLAIR					
Axial: T1(W)					
Axial: T2(W)					

Figure 1e: Examples of segmented output of the MR brain image with low-grade tumor acquired from BraTS 2013 dataset.

Table 1: Assessment comparison of the key parameters of JAYA-FCM

Parameters	FCM	PSO with FCM	JAYA with FCM
Similarity Index	0.7985	0.9011	**0.9740**
Sensitivity	0.7992	0.8701	**0.9710**
Specificity	0.7126	0.7926	**0.9130**
Time requirement (in Seconds)	24.77	22.35	**3.14**
Memory usage (in Megabytes)	432×10^5	1550×10^5	**834**

5.2. Minimally parametrized segmentation framework with dual metaheuristic optimization algorithms and FCM for detection of anomalies in MR brain images

This research emphasises brain tumour region detection using Fuzzy C-Means (FCM) clustering techniques and segmented output enhancement using two different optimization techniques, namely, Artificial Bee Colony (ABC) and the JAYA algorithm. This methodology first deploys the FCM clustering technique to segment the tumour region in the MRI. Then, the initial stage of optimization is done using the ABC algorithm with the help of texture features extracted from the segmented image through the Gray Level Co-occurrence Matrix (GLCM) technique. Lastly, a novel JAYA algorithm is deployed for the second stage of optimization to provide precise segmentation with the support of global and local best solutions.

The key contribution and novelty of this work is deploying two different metaheuristic optimization techniques with key amendments at different stages. The

proposed framework delivers high accuracy in tumour detection, competing with the contemporary methods used for the evaluation of MR brain images.

Figures 2a to 2e portray the dissection outcomes of MR brain images from clinical, Harvard Brain Web Repository, and BraTS-2013 datasets, respectively. The performance measures attained from the proposed method are exemplified in Table 2.

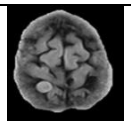
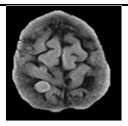
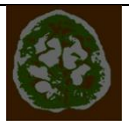
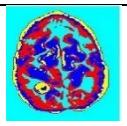
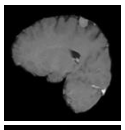
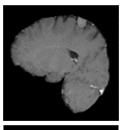
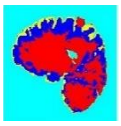
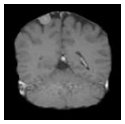
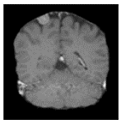
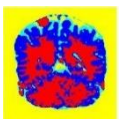
Image Planes	Input Image	Filtered Image	FCM Output	JAYA-ABC FCM Output
Axial T2-W				
Sagittal T1-W				
Coronal T1-W				

Figure 2a: Segmentation output of MR brain images for Meningioma carcinoma

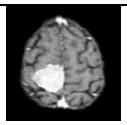
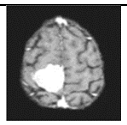
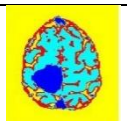
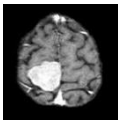
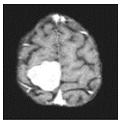
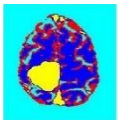
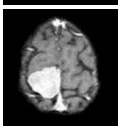
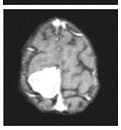
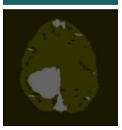
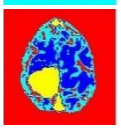
Image Planes	Input Image	Filtered Image	FCM Output	JAYA-ABC FCM Output
Axial - CE T1-W				
Axial - CE T1-W				
Axial - CE T1-W				

Figure 2b: Segmented output results of low and high-grade gliomas in MR images

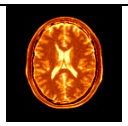
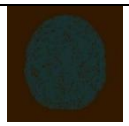
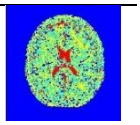
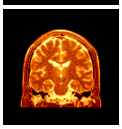
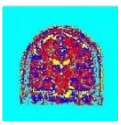
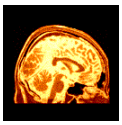
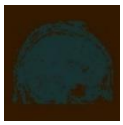
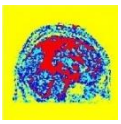
Image Planes	Input Images	FCM	JAYA-ABC-FCM
Axial (or) Transverse			
Coronal			
Sagittal			

Figure 2c: Segmented output of the proposed algorithm processed on T2-Weighted images with a 5% noise level.

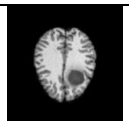
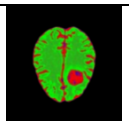
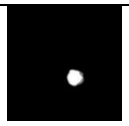
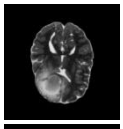
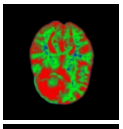
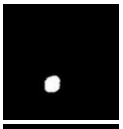
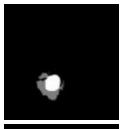
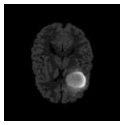
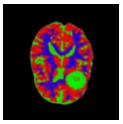
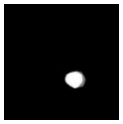
Image Planes	Input Image	FCM output	JAYA-ABC FCM Output	ROI Extracted Tumour Region	Ground Truth Image
Axial: T1(W)					
Axial: T2(W)					
Axial: FLAIR					

Figure 2d: Segmented output of the proposed novel JAYA-ABC framework processed on high-grade brain tumour images

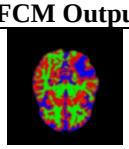
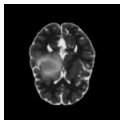
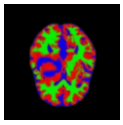
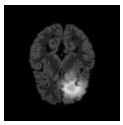
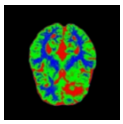
Image Planes	Input Image	FCM output	JA-ABC FCM Output	ROI Extracted Tumour Region	Ground Truth Image
Axial: T1(W)					
Axial: T2(W)					
Axial: FLAIR					

Figure 2e: Segmented output of the proposed novel ABC-JAYA framework processed on low grade brain tumour images

Table 2: Assessment comparison of the key parameters of JAYA-ABC-FCM

Parameters	FCM	PSO with FCM	JAYA with FCM	JAYA –ABC with FCM
Similarity Index	0.7985	0.9011	0.9740	**0.9870**
Sensitivity	0.7992	0.8701	0.9710	**0.9812**
Specificity	0.7126	0.7926	0.9130	**0.9545**
Time requirement (in Seconds)	24.77	22.35	3.14	**3.85**
Memory usage (in Megabytes)	432	1550	834	**1021**

5.3. Tumour region detection in MR brain images using MFCM based segmentation and Self Accommodative JAYA based optimization

This work's major objective is to improve multi-region detection performance by combining a modified Fuzzy C-Means (FCM) with a self-accommodative JAYA (SAJAYA) algorithm. Due to its capacity to choose the number of cluster heads in the

FCM stage and population suitability in the optimization stage, this technique is more successful and considerably facilitates precise MR brain image segmentation.

To achieve the best performance, self-accommodative JAYA algorithm is employed to optimize segmentation variables and reduce the overall computation time and complexity. The proposed algorithm segments the different informative sections, such as cerebrospinal fluid, grey matter, and white matter, which will be most helpful to investigate and characterise the tumour.

This work is divided into two sections. In the first, the modified FCM function is improved with cluster head determination capability. Second, a dynamic sub-population is used to improve the search operation of SAJAYA optimization. The experiment's findings show that the suggested algorithm is successful in terms of sensitivity, specificity, accuracy, and other benchmark metrics. Figures 3a to 3e present an opulent explanation of the segmentation results offered by the Java-based modified FCM.

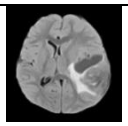
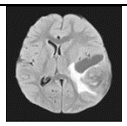
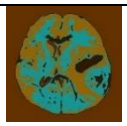
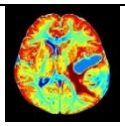
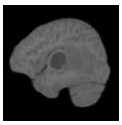
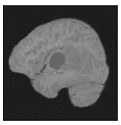
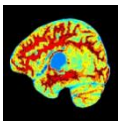
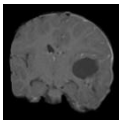
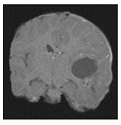
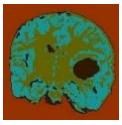
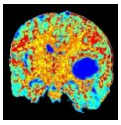
Image Planes	Input Image	Filtered Image	FCM Output	MFCM Output	SAJAYA-MFCM Output
Axial T2-W					
Sagittal T1-W					
Coronal T1-W					

Figure 3a: Final segmented output of MR brain images for Primitive Neuro Ectodermal Tumour

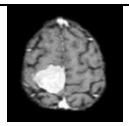
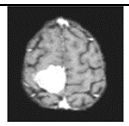
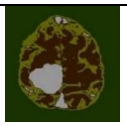
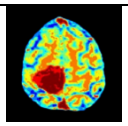
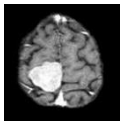
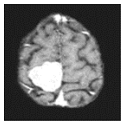
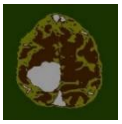
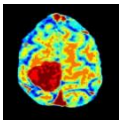
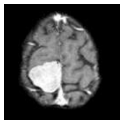
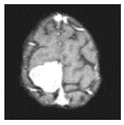
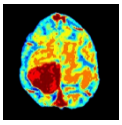
Image Planes	Input Image	Filtered Image	FCM Output	MFCM Output	SAJAYA-MFCM Output
Axial - CE T1-W					
Axial - CE T1-W					
Axial - CE T1-W					

Figure 3b: Segmented output results of gliomas in MR brain images

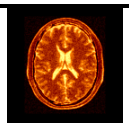
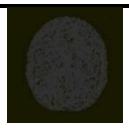
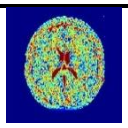
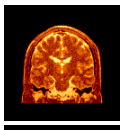
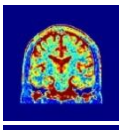
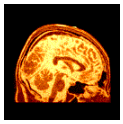
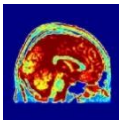
Image Planes	Input Image	FCM Output	MFCM Output	SAJAYA-MFCM Output
Axial (or) Transverse				
Coronal				
Sagittal				

Figure 3c: Segmented output of the proposed algorithm processed on T2-Weighted images with a 9% noise level

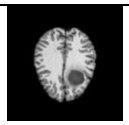
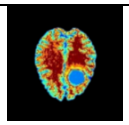
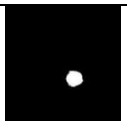
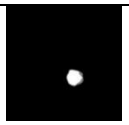
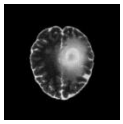
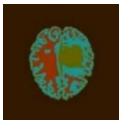
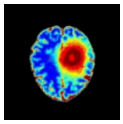
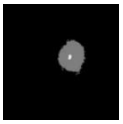
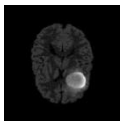
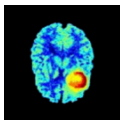
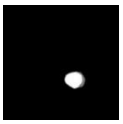
Image Planes	Input Images	MFCM	JAYA-MFCM Results	Detected Tumor region	Ground Truth Images
Axial: T1(W)					
Axial: T2(W)					
Axial: FLAIR					

Figure 3d: Examples of segmented output of the MR brain image with high-grade tumor acquired from BRATS 2013 dataset.

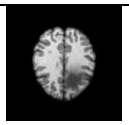
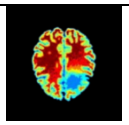
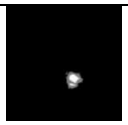
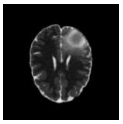
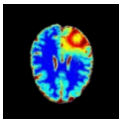
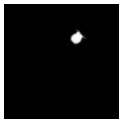
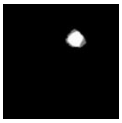
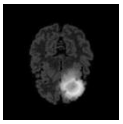
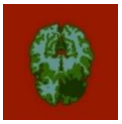
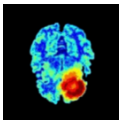
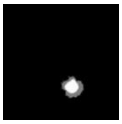
Image Planes	Input Images	FCM	SAJAYA-MFCM Results	Detected Tumor Region	Ground Truth Images
Axial: T1(W)					
Axial: T2(W)					
Axial: FLAIR					

Figure 3e: Examples of segmented output of the MR brain image with low-grade tumor acquired from BRATS 2013 dataset using SAJAYA MFCM.

Though several of the algorithms have been developed and their eventual combinations are available, a combination of the technique named SAJAYA-MFCM is still in non-existence.

This section explores the quantitative assessment of the suggested MR brain images carrying different tumour complaints. The performance of the JAYA-FCM, JAYA-ABC-FCM, and SAJAYA-MFCM algorithms is comprehensively compared with various standalone and integrated algorithms to understand the progressive improvement achieved by the recommended novel SAJAYA-MFCM towards tumour region identification. Out of them, the SAJAYA-MFCM method delivers better outcomes compared to other hybrid methodologies. The performance measures of the proposed SAJAYA MFCM method are described in Table 3.

Table 3: Assessment comparison of the key parameters of SAJAYA-MFCM

Parameters	FCM	PSO with FCM	JAYA with FCM	JAYA –ABC with FCM	SAJAYA – MFCM
Similarity Index	0.7985	0.9011	0.9740	0.9870	**0.9881**
Sensitivity	0.7992	0.8701	0.9710	0.9812	**0.9835**
Specificity	0.7126	0.7926	0.9130	0.9545	**0.9745**
Time requirement (ir Seconds)	24.77	22.35	3.14	3.85	**2.88**
Memory usage (in Megabytes)	432	1550	834	1021	**772**

5.4. Comparison of the suggested methodologies with recently developed and traditional algorithms.

All three suggested techniques' segmented results were shown in Figure 4a to 4e for visual comparison.

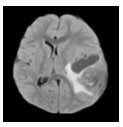
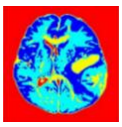
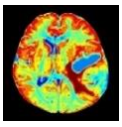
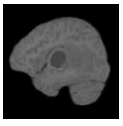
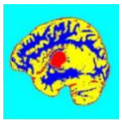
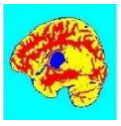
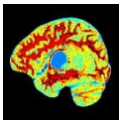
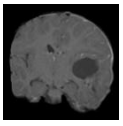
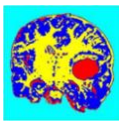
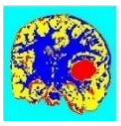
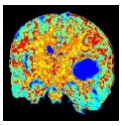
Image Type	Input Images	JAYA FCM	JAYA-ABC-FCM	JAYA-MFCM
Axial: T2 (W)				
Sagittal: T1 (W)				
Coronary: T1 (W)				

Figure 4a: comparison of segmentation outcomes of all three proposed algorithm.

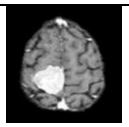
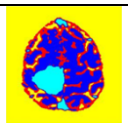
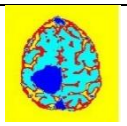
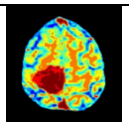
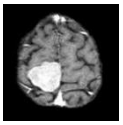
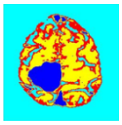
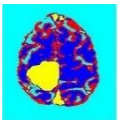
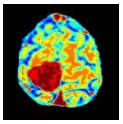
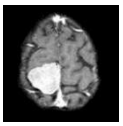
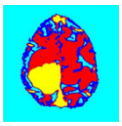
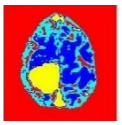
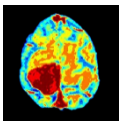
Image Planes	Input Image	JAYA-FCM Output	JAYA-ABC FCM Output	SAJAYA-MFCM Output
Axial: T1 (W)				
Axial: T1 (W)				
Axial: T1 (W)				

Figure 4b: Visual assessment of the segmented results of the suggested methods for high-grade gliomas in MR brain images

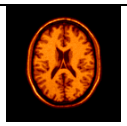
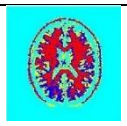
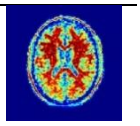
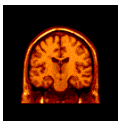
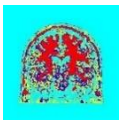
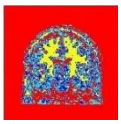
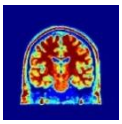
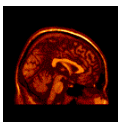
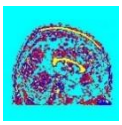
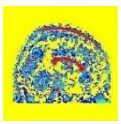
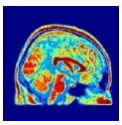
Image Planes	Input Images	JAYA-FCM Output	JAYA-ABC-FCM	SAJAYA-MFCM
Axial (or) Transverse				
Coronal				
Sagittal				

Figure 4c: Comparison of segmented output of the proposed algorithms processed on T1-Weighted images with a 5% noise level

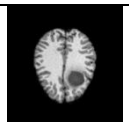
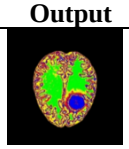
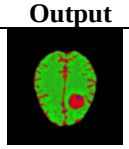
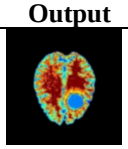
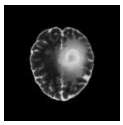
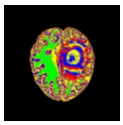
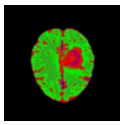
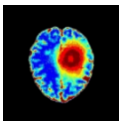
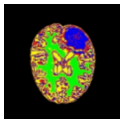
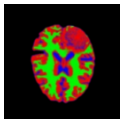
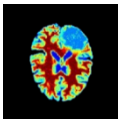
Image Planes	Input Images	JAYA-FCM Output	JAYA ABC FCM Output	MFCM	SAJAYA-MFCM Output
Axial: T1(W)					
Axial: T2(W)					
Axial: T2(W)					

Figure 4d: Assessment of the suggested methods for BraTS 2013 high grade tumour dataset

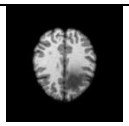
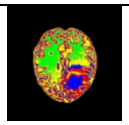
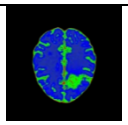
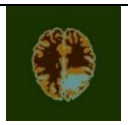
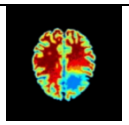
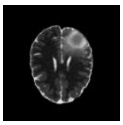
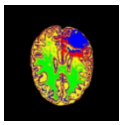
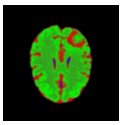
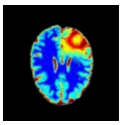
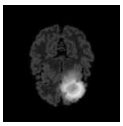
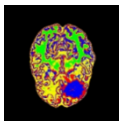
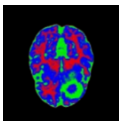
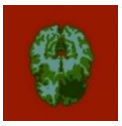
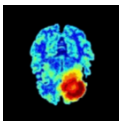
Image Planes	Input Images	JAYA-FCM Results	JAYA ABC FCM Results	MFCM	SAJAYA-MFCM Results
Axial: T1(W)					
Axial: T2(W)					
Axial: FLAIR					

Figure 4e: Assessment of the suggested methods for BraTS 2013 low grade tumour dataset

This study unfolds the information present in the medical images, especially the brain MRI, so that the doctors are quite convenient while diagnosing the complex anomalies present.

In conclusion, the proposed SAJAYA-MFCM combination delivers remarkable outcomes in segmenting the anomalies present in the MRI as exhibited in Figures 4a to 4e. By contrasting the SAJAYA MFCM algorithms with other developed algorithms, their superiority is demonstrated and highlighted in Figure 5 with bold face.

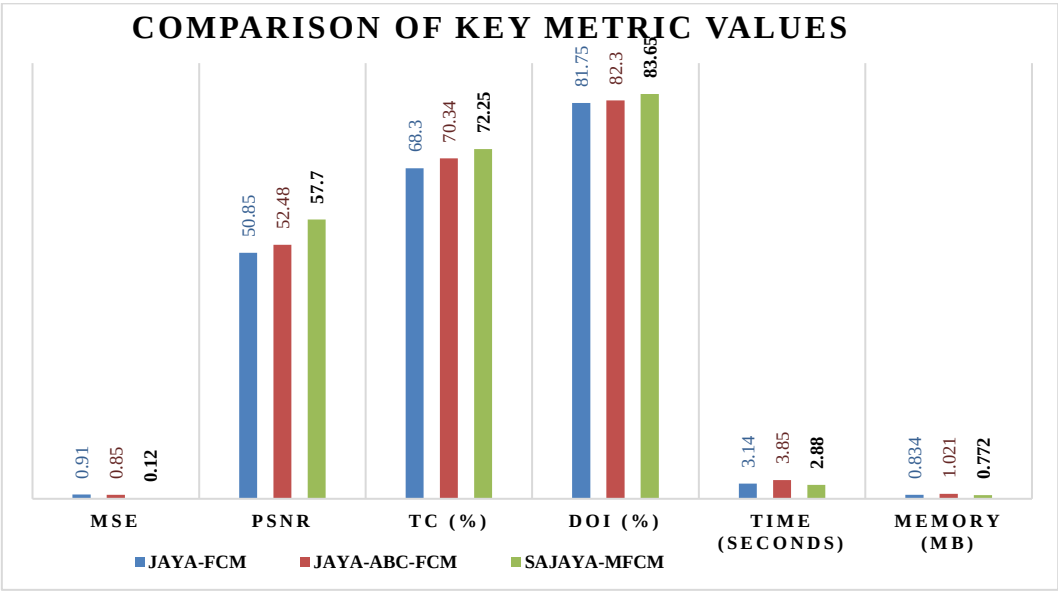


Figure 5: Comparison of the performance measures of all proposed methods

6. CONCLUSION

The key advantage of the suggested methodology is that it produces superior segmentation results because it is less sensitive to the initial cluster head position. The resultant outcome confirms the effectiveness of the suggested algorithm and is proven via key benchmark evaluation metrics. When compared to the other two approaches recommended, the SAJAYA-MFCM method provides notable segmentation results across clinical and BraTS datasets while requiring minimal computational time and memory, which are critical requirements for medical practitioners to have a better understanding of tumour regions during pre- and post-treatment procedures and ultimately assist patients in making a good and speedy recovery. It is evident that the suggested SAJAYA-MFCM approach is successful in addressing medical image optimization issues and is a revival contender for the existing methodologies. We believe that the SAJAYA MFCM algorithm can aid radiologists in the more effective and precise diagnosis of brain tumour disorders.

7. ORGANIZATION OF THE THESIS

The thesis is organized as follows: The first chapter examines brain tumours in detail, including their various types, occurrences, and the role of MR imaging in identifying the lesion. The second chapter explicitly describes various MR brain segmentation and optimization algorithms that have been developed, as well as their performance in comparison to other computing techniques available in the literature. Chapter 3 provides details on the data samples collected from the diagnosis centre and other web sources (BraTS 2013 dataset).

Chapter 4 compares the performance of the fuzzy-based segmentation, GLCM-based feature extraction technique, and JAYA and ABC optimization techniques used in the thesis to delineate tumour regions to other computing techniques available in the literature. Chapter 5 explains the operation and highlights of the FCM-based JAYA algorithm used to segment MR brain clinical and BraTS dataset images.

This elucidates the FCM-based novel double optimization framework developed by combining the JAYA and ABC algorithms and their respective outcomes on clinical and BraTs datasets. Chapter 7 describes the operation and outcomes of the SAJAYA-based MFCM algorithm, which initially alters the standard positioning of the

cluster head and then further refines the optimal value derived from SAJAYA optimization for better segmentation of the tumour from MRI images.

The comparison of all three techniques suggested in this thesis for segmenting the tumour from MRI images is covered in Chapter 8. A thorough quantitative and qualitative analysis has been conducted for the proposed methodologies. The research is concluded in Chapter 9, which also reviews and identifies the most effective algorithm for segmenting MR brain images out of those suggested in this thesis. Additionally, the future work scope was discussed in light of the thesis' findings.

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List of Publications

1. N.Senthilkumar, G. Vishnuvarthanan, R. Rao, Z. Yu-Dong, M. Pallikonda Rajasekaran, K. Karunanithi, and K. Ejaz, A novel triple-level combinational framework for brain anomaly segmentation to augment clinical diagnosis, *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, **10 (**1) (2022), 96-111.

2. N.Senthilkumar, G. Vishnuvarthanan, M. Pallikonda Rajasekaran, Z. Yu-Dong, B. Kannapiran, K. Karunanithi, and K. Ejaz, Minimally parametrized segmentation framework with dual metaheuristic optimization algorithms and FCM for detection of anomalies in MR brain images, *Biomedical Signal Processing and Control* **78** (2022), 103866.

3. N.Senthilkumar, G. Vishnuvarthanan, M. Pallikonda Rajasekaran, Z. Yu-Dong, and T. ArunPrasath, Tumour region detection in MR brain images using MFCM based segmentation and Self Accommodative JAYA based optimization, *2023 3rd International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS)*, (2023), 340-345.